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Research on Reservoir Parameter Inversion Method Based on P-S Model and PSO Algorithm

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Abstract

Dielectric Scanner can obtain multi-frequency dielectric constant and conductivity information, which provides a new technical means for fluid identification and oil and gas saturation evaluation of complex reservoirs. The saturation calculation based on dielectric dispersion is a problem of solving complex implicit functions and there are many parameters to be inverted. The traditional method has the problems of low efficiency, easy to fall into local optimum and insufficient anti-noise.In this paper, the shale reservoir is taken as the research object, and the research is carried out around the evaluation method of oil and gas saturation. Based on the P-S dispersion model, the PSO (Particle Swarm Optimization) particle swarm optimization algorithm is used to carry out the inversion of oil and gas saturation and related reservoir parameters. The accuracy, timeliness, stability and applicability of the method for reservoir parameter inversion in the P-S dispersion model are analyzed. In terms of accuracy, the accuracy of reservoir parameter inversion can reach more than 99 % in the absence of noise. In terms of timeliness, the processing process of PSO algorithm belongs to the iterative optimization of sample by sample, so the processing time of PSO algorithm is linearly related to the number of samples. Then, combined with the prediction results at 1 %, 3 %, 5 % and 10 % noise levels, it is shown that the proposed method has better inversion performance under the condition of 5 % noise. As the noise becomes larger, the inversion accuracy decreases, and there are differences between different parameters. The established evaluation method has certain application potential, which can provide theoretical basis and technical support for the fine evaluation of shale oil and gas reservoirs..

Keywords

P-S dispersion model ; PSO algorithm ; Shale ; Oil and gas saturation evaluation.

1. Introduction

Multi-frequency dielectric logging information is rich, including 4 dielectric constants and 4 conductivity[1]. However, the saturation calculation based on dielectric dispersion is a problem of solving complex implicit functions[2]. There are many parameters to be inverted for such problems. The traditional saturation inversion method is slow and the interpretation accuracy is poor[3]. It is necessary to study the saturation inversion method with high efficiency and high precision.

The limitations of traditional inversion methods are mainly reflected in: based on simplified rock physics models, it is difficult to accurately describe complex nonlinear relationships. These methods are sensitive to the initial value and easy to fall into the local optimal solution ; it performs poorly in dealing with multi-parameter coupling problems and is sensitive to noise. In view of these problems, this chapter will systematically study the suitable method: PSO (Particle Swarm Optimization) particle swarm optimization algorithm. As a global optimization algorithm, PSO algorithm has the characteristics of high search efficiency and strong robustness,

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and is especially suitable for dealing with multi-extremum optimization problems. In this paper, the above methods will be introduced on the basis of the dielectric dispersion model to carry out reservoir parameter inversion research. The principles, implementation steps and application characteristics of the two methods are described in detail, and the effectiveness and applicability of the method in the P-S dielectric dispersion model are verified by comparative analysis.

2. P-S dispersion model

2.1. PPIP phenomenon

PPIP (Perfectly Polarized Interfacial Polarization) refers to the interfacial polarization phenomenon when conductive particles are dispersed in electrolyte-saturated porous media without redox reaction. This phenomenon is usually studied by conducting spherical particles uniformly distributed in the electrolyte host medium. Due to the symmetry of spherical particles, the interfacial polarization response is not related to the direction of the applied electric field macroscopically, but it is still manifested in the directional migration of carriers and the accumulation of interfacial charge at the microscopic level. When the applied electric field acts on the conductive particles, the carriers inside the particles will redistribute along the direction of the electric field, in which different types of charge carriers migrate in the opposite direction and accumulate on both sides of the solid-liquid interface between the conductive particles and the surrounding electrolyte. Since these charges cannot continue to transmit through the interface, an obvious charge separation phenomenon will be formed at the interface, which will induce interface polarization. This polarization phenomenon formed by carrier migration and interfacial charge accumulation in conductive particles is called fully polarized interfacial polarization, namely PPIP phenomenon. As shown in Fig.1, the fully polarized interfacial polarization mechanism of conductive spherical particles in the electrolyte under the action of an applied electric field is shown. The carriers inside the conductive particles migrate directionally under the action of electric field and accumulate on both sides of the solid-liquid interface, thus forming charge separation and inducing interface polarization.

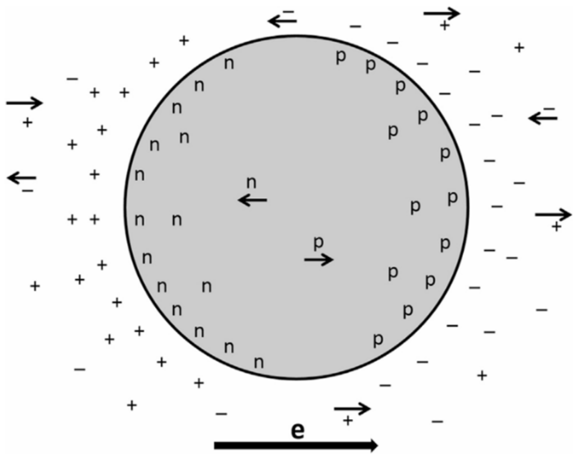

Fig. 1 PPIP phenomenon

2.2. SCAIP phenomenon

For surface charged non-conductive particles, such as clay minerals and sand, the surface is usually negatively charged. These surface negative charges will attract the cations in the surrounding electrolyte solution, causing them to gather near the surface of the particles to form a counter-ion layer. The formation of the counterion layer is related to ion adsorption, protonation / deprotonation of surface hydroxyl groups, and dissociation of other active surface groups. When the external electromagnetic field acts on the system, the cationic counterion layer distributed on the surface of the non-conductive particles will migrate directionally along the direction of the electric field, resulting in the redistribution of charge at the solid-liquid interface and the formation of net charge accumulation and charge separation on both sides of the interface. The enhanced interfacial polarization due to the participation of surface conductance is called surface-conductance-assisted interfacial polarization (SCAIP). For the spherical non-conductive particles uniformly distributed in the electrolyte, due to the spherical symmetry of the particles, the interfacial polarization response is macroscopically independent of the direction of the applied electric field, but microscopically it still shows that the counterion layer migrates along the direction of the electric field and forms polarization charge accumulation on both sides of the particles. The SCAIP phenomenon shows that even if the particle itself is not conductive, as long as its surface is charged and there is an anti-ion layer, it can also produce a significant interfacial polarization response under the action of an applied electric field. As shown in Figure 2, the SCAIP mechanism of non-conductive spherical particles with surface charge in the electrolyte under the action of an applied electric field is illustrated. The negative charge on the surface of the particles attracts the surrounding cations to form an anti-ion layer. Under the action of the electric field, the anti-ion layer migrates along the direction of the electric field, and finally forms charge accumulation on both sides of the solid-liquid interface and induces interface polarization.

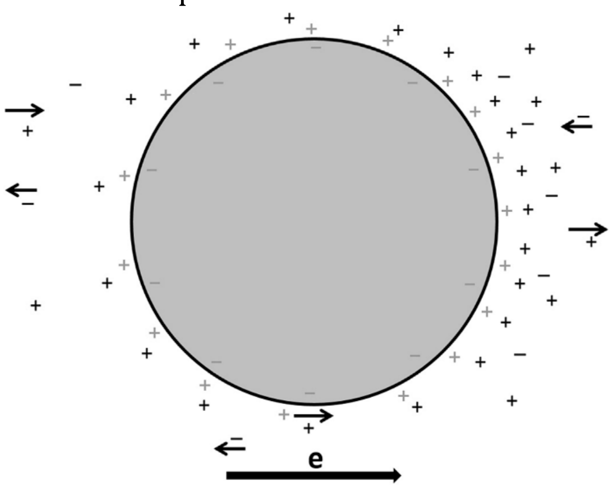

Fig. 2 SCAIP phenomenon

2.3. P-S model

For the mixture containing spherical conductive and non-conductive particles, the PPIP model will be combined with the SCAIP model[4]. For example, pyrite-rich argillaceous sandstones contain pyrite particles, clay-sized particles, sand-sized particles, and clay particles[5]. Consider the presence of oil and electrolyte in the pores of the main medium. It is assumed that the oil is distributed in the mixture in the form of spherical droplets and can be regarded as a non-conductive spherical inclusion phase with negligible surface charge. It is also assumed that the inclusion phase is mainly hydrophilic[6]. The effective medium formula for the complex conductivity response of the PPIP-SCAIP (P-S) model can be expressed as follows:

$$\frac{\sigma_{eff}^{*}-\sigma_{h}^{*}}{\sigma_{eff}^{*}+2\sigma_{h}^{*}}=\sum\phi_{cond}f_{cond}\left(\omega\right)+\sum\phi_{ncond}f_{ncond}\left(\omega\right)+\phi_{o}f_{o}\left(\omega\right) \tag{1}$$

3. Research on reservoir parameter inversion method based on P-S model and PSO algorithm

PSO algorithm is a typical swarm intelligence optimization method. Its basic idea comes from the information sharing and collaborative search mechanism among individuals in the process of bird foraging[7]. In the PSO algorithm, each particle represents the candidate solution, and the particle describes its search state through two variables: velocity and position. In the iterative process, on the one hand, the particle performs local search according to its own historical optimal position, on the other hand, the PSO algorithm is adjusted according to the historical optimal position of the group. It is a stochastic optimization algorithm that simulates the cooperative behavior of biological groups. The algorithm regards each potential solution as a particle in the search space and assigns its position and velocity attributes. In the search process, the particle continuously adjusts the motion direction and step size according to its own historical optimal position and the group 's historical optimal position, so as to gradually approach the optimal solution of the problem. The search process of PSO algorithm does not need the derivative information of the objective function, which is especially suitable for solving complex nonlinear, multi-peak and high-dimensional optimization problems. In reservoir parameter inversion, the parameter combination to be solved can be regarded as particle position[8]. The error between the forward response and the measured response is constructed as a fitness function, and the parameters are solved by particle swarm iterative search.

3.1. Parameter setting

The inversion performance of the PSO algorithm mainly depends on the setting of the core parameters. Combined with the requirements of the P-S dispersion model inversion, the core parameters of the PSO algorithm in this paper are determined through multiple debugging. The specific parameters and values, and the setting basis are shown in Table 1. The parameter settings correspond to the core configuration in the experimental code.

Table 1 Parameter setting

Parameter name	Value
The learning factor C1	1.49445
The learning factor C2	1.49445
Maximum number of iterations	100
Population size	50
Upper speed limit	0.1
Lower limit of velocity	-0.1

The inversion parameter setting of the dispersion model: Combined with the previous parameter sensitivity analysis results, it can be seen that the water porosity, clay volume fraction and pyrite volume fraction have a significant effect on the dispersion response of the P-S model. The water-bearing porosity mainly controls the proportion of the host phase, which has a direct impact on the overall conductivity level and dielectric response strength. The volume fraction of clay will change the surface polarization contribution of non-conductive particles. The volume fraction of pyrite will enhance the polarization effect of conductive particles and have a significant impact on the low-frequency and mid-frequency response. In this section, the other parameters are fixed in the virtual sample inversion. The following three parameters are selected as the inversion variables at the four frequency points of 20 MHz, 100 MHz, 350 MHz and 1 GHz:

$$X = \left[por\_w, por\_c, por\_p \right] \tag{2}$$

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In the formula, por_w represents water porosity, por_c represents clay content, por_p represents pyrite content, and the volume fraction of each phase should also satisfy the total volume conservation constraint. The total volume fraction is less than or equal to 1.

Here, the search range of the parameters to be inverted is set as table 2, and the position update of the particles is always constrained within the above search range to ensure the physical rationality of the inversion parameters.

Table 2 Parameter search range

Parameter	Search Lower Limit	Search Upper Limit
Water-bearing porosity	0	0.5
Clay content	0	0.5
Pyrite content	0	0.5

3.2. Objective function construction and iterative optimization

Let the parameter vector corresponding to the current position of the particle be:

$$X = [por\_w, por\_c, por\_p] \tag{3}$$

After substituting it into the P-S forward model, the predicted relative permittivity and predicted conductivity at four frequency points can be obtained:

The corresponding observations are recorded as: ε_r^{obs} , σ^{obs}

In order to comprehensively consider the fitting degree of dielectric constant and conductivity at all frequency points, this paper uses the relative error form to construct the objective function. Firstly, the relative error vectors of dielectric constant and conductivity are calculated respectively:

$$e_\varepsilon = \frac{\varepsilon_r^{pre} - \varepsilon_r^{obs}}{\varepsilon_r^{obs}}, e_\sigma = \frac{\sigma^{pre} - \sigma^{obs}}{\sigma^{obs}} \tag{4}$$

Then the two types of errors are spliced into an overall error vector, and its second norm is taken as the fitness value:

$$F(X) = \left\| \begin{bmatrix} e_\varepsilon \\ e_\sigma \end{bmatrix} \right\|_2 \tag{5}$$

The smaller the fitness value is, the closer the prediction curve generated by the current parameter combination is to the observation curve.

Iterative optimization process: In each iteration, the program first updates the speed according to the current particle state, and then updates the position using the new speed. Its update formula is:

$$v_i^{k+1} = wv_i^k + c_1 r_1 (p_i^k - x_i^k) + c_2 r_2 (g^k - x_i^k) \tag{6}$$

$$x_i^{k+1} = x_i^k + v_i^{k+1} \tag{7}$$

The individual learning item is the ability to reflect the particle 's ability to move closer to its own historical optimal position ; the group learning item is the ability to reflect the particle 's ability to move closer to the global optimal position. The three work together to make the particle swarm not only have global search ability, but also have certain local development ability.

When all particles complete a new round of position update, the program calls the fitness function again to calculate the current error value of each particle. When the fitness of a particle is better than its historical individual optimal fitness, the current particle position is used to replace its individual optimal position ; when the fitness is better than the global optimal fitness of the entire population, the global optimal position is updated:

$$\begin{aligned} &\text{if } F(x_i^{k+1}) < F(p_i^k),\ p_i^{k+1} \equiv x_i^{k+1} \\ &\text{if } F(x_i^{k+1}) < F(g^k),\ g^{k+1} \equiv x_i^{k+1} \end{aligned} \tag{8}$$

By repeating this process, the particle swarm will gradually converge to the optimal parameter region. After reaching the set maximum number of iterations, the final value is output and the optimal solution is output.

3.3. Analysis of reservoir parameter inversion results

In order to verify the effectiveness of the reservoir parameter inversion method based on P-S dispersion model and PSO algorithm, this paper first uses virtual samples to test. Virtual sample refers to the dispersion response data calculated by the P-S forward model under the condition of known model parameters, and input it into the inversion program as the observation data. Since the real parameters of the sample are known, the difference between the inversion results and the real values can be directly compared, so as to quantitatively evaluate the ability of PSO to identify the parameters of the P-S model.

Analysis of single group virtual sample processing results:

In order to intuitively explain the PSO algorithm 's inversion process of reservoir parameters in the P-S model, a set of virtual samples is first selected for testing. Set a set of real parameter vectors to be:

$$X_{\text{true}} = \left[por\_w, por\_c, por\_p \right] \tag{9}$$

After substituting it into the P-S forward model, the relative dielectric constant and conductivity response at four frequency points are obtained, and the response is input into the PSO algorithm as the inversion target data. Through iterative optimization, the optimal parameter vector Xbest can be obtained. Here, it takes 0.22 seconds to process a set of samples.

The processing results are as follows: Table 3, the prediction accuracy of PSO algorithm for three reservoir parameters can reach 99 %:

Table 3 Comparison of the predicted values of the three parameters and their relative errors

Parameter	True value	Predicted value	Relative error
Water-bearing porosity	0.1	0.1	0%
Clay content	0.1	0.0999	0.1%
Pyrite content	0.1	0.0999	0.1%

As shown in Figure 3, the optimal fitness value gradually decreases with the increase of the number of iterations, and the overall trend shows a rapid decline first, then a slow convergence and finally tends to be stable.

In the first 10 iterations, the optimal fitness value decreases rapidly from the initial large value to the lower level, indicating that the particle swarm can quickly lock the potential optimal region by using the group cooperative search mechanism, and has strong global optimization ability. As the iteration continues, the decline rate of the fitness value gradually slows down, and the curve shows a local stepwise decline, which indicates that the algorithm has entered the local fine search stage, and the particles constantly adjust their positions near the optimal solution to improve the parameter identification accuracy. After about the 50 th iteration, the optimal fitness value is close to 0, and the curve is basically stable, indicating that the algorithm has reached a stable convergence state.

It can be seen that the PSO algorithm has better convergence stability and higher solution efficiency in the inversion process. This method can obtain better optimization results in fewer iterations.

From the physical point of view, the successful inversion of a single set of samples shows that under the condition of given frequency points and fixed model parameters, the comprehensive influence of water porosity, clay volume fraction and pyrite volume fraction on the dispersion curve can be effectively identified by PSO algorithm. The PSO algorithm can not only find the solution with smaller error in the parameter space, but also the dispersion curve corresponding to the parameter combination has a good matching relationship with the target data.

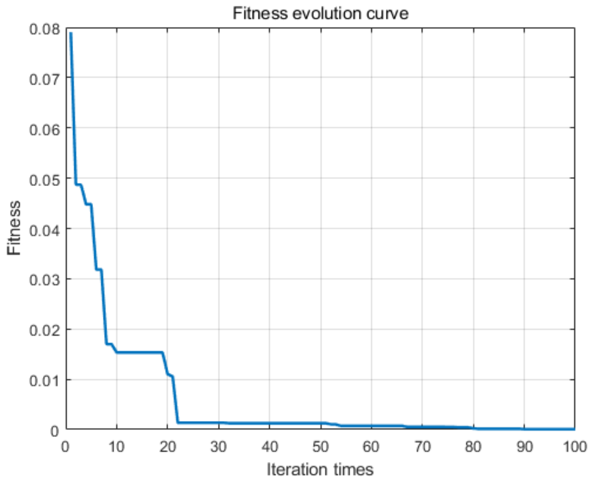

Fig. 3 Fitness evolution curve

Analysis of multi-group virtual sample processing results:

In order to further investigate the stability of the inversion method, multiple sets of virtual samples are randomly generated within the preset parameter range, and independent inversion is performed on each set of samples. Assuming that the total number of virtual samples is 100, each group of samples contains a set of real parameters and their corresponding four frequency points of conductivity and dielectric constant response. After predicting all samples group by group, the corresponding prediction parameter results can be obtained. Here, 100 sets of samples are processed in 22 seconds.

As shown in Fig.4, the comparison between the real value and the predicted value shows that the scatter points of the three parameters are basically distributed along the 45 ° reference line, indicating that the predicted value is highly consistent with the real value, indicating that the established inversion method can accurately predict the reservoir parameters under the condition of virtual samples.

The three-parameter inversion method based on P-S model and PSO algorithm has good feasibility under the condition of virtual sample. The joint constraint of multi-frequency dielectric constant and conductivity enhances the identifiability of model parameters, so that the water-bearing porosity, clay and pyrite volume fraction can obtain more accurate inversion results.

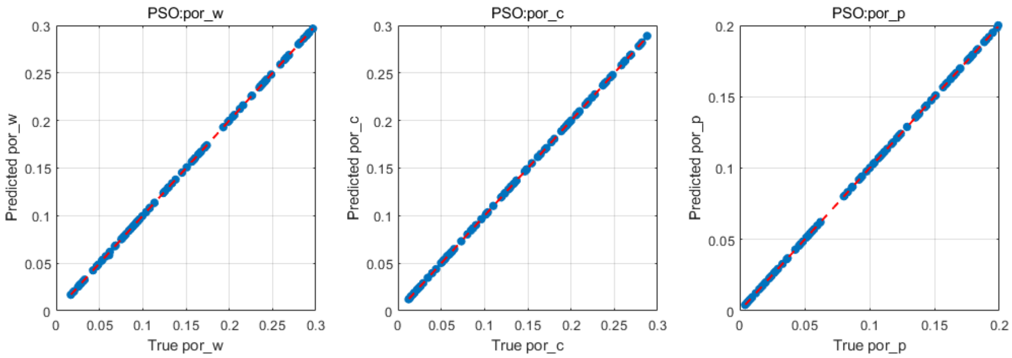

Fig. 4 The scatter distribution of predicted value and real value of PSO algorithm

Timeliness analysis:

In addition to the inversion accuracy, timeliness is also an important indicator of application value. The PSO algorithm belongs to the sample-by-sample optimization solution method, that is, each set of observation data needs to independently complete the process of particle initialization, fitness calculation, speed update, position update, and optimal solution search. Therefore, the total calculation time is approximately linear with the number of samples.

For a single set of samples, the inversion of parameters by PSO algorithm can usually complete the parameter search in a short time and obtain high-precision inversion results. However, when the number of samples increases, the total time consumption will increase significantly. If the inversion time of a single set of samples is about t seconds, the total time of N sets of samples can be roughly expressed as:

$$T \approx N \times \mathrm{t} \tag{10}$$

This shows that the PSO algorithm has good applicability when dealing with a small number of samples, but its computational efficiency will be limited in large-scale batch inversion.

Anti-interference ability analysis:

As shown in Figure 5, 100 sample points are taken to make a scatter distribution map for analysis. From the overall trend, as the noise level increases from 1 % to 10 %, the three-parameter inversion scatter gradually changes from a concentrated distribution to a discrete distribution, indicating that the noise will weaken the dispersion. The mapping stability between the response and the model parameters leads to a decrease in inversion accuracy. There are obvious differences in the sensitivity of different parameters to noise, showing different anti-interference characteristics.

At the 1 % noise level, the scatter points of the three parameters are close to the 45 ° reference line as a whole, indicating that the inversion results still have high accuracy. Among them, the scatter points of por-p are the most concentrated, almost all of which are distributed near the reference line, indicating that the volume fraction of pyrite has the best identifiability under weak noise conditions. The inversion results of por-w are also relatively stable. Most of the sample points are in good agreement with the reference line, and there are slight deviations at individual points. In contrast, por-c has begun to appear a certain degree of dispersion, indicating that the clay volume fraction is more sensitive to noise, and will be affected even at lower noise levels.

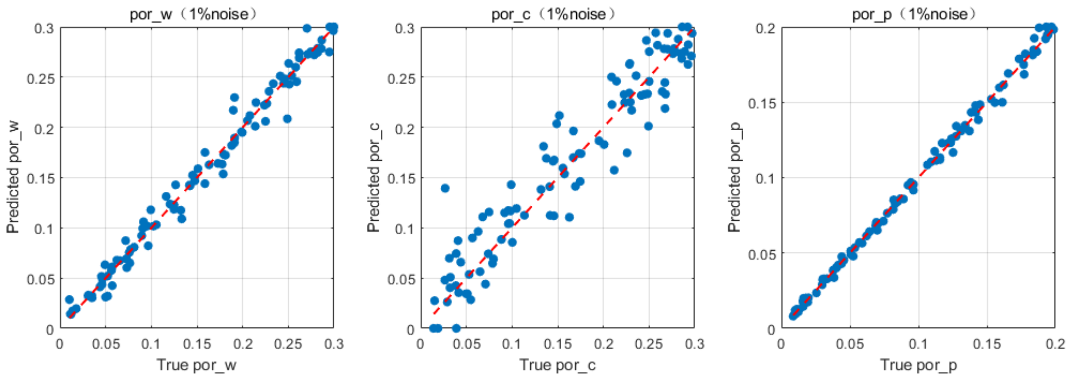

Fig. 5 Scatter point distribution under 1 % noise

As shown in Figure 6, when the noise is increased to 3 %, por-w and por-p still maintain a good linear correspondence, but the degree of scatter dispersion is significantly increased compared to 1 % noise, indicating that the inversion accuracy has decreased. In particular, por-w has a certain offset in some high-value areas. Although por-p is also affected by noise, it can still maintain a good fitting trend, indicating that its anti-interference ability is relatively strong.

In contrast, the scatter dispersion of por-c is further aggravated, some sample points have obviously deviated from the reference line, and there are large errors in the low value area and the high value area. This indicates that the stability of clay volume fraction is weak at medium noise level, and its inversion results are more susceptible to noise disturbance.

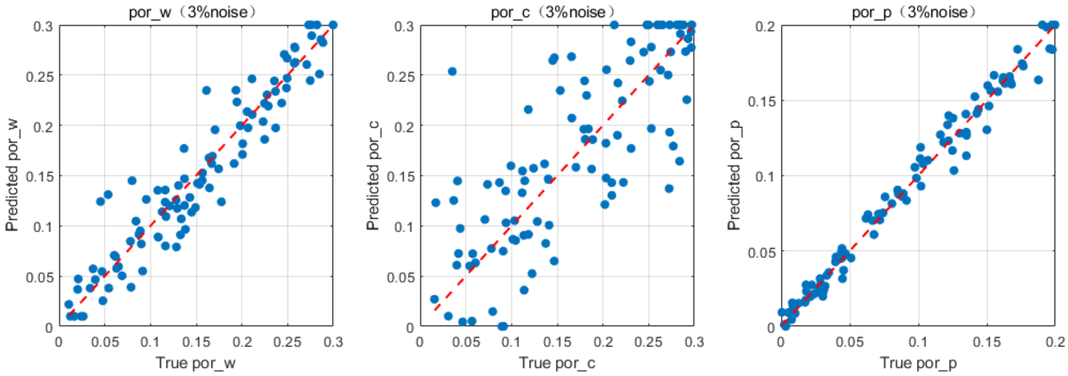

Fig. 6 Scatter point distribution under 3 % noise

As shown in Fig 7, under the condition of 5 % noise, the accuracy of three-parameter inversion is further reduced, especially the scatter distribution of por-w and por-c has become obviously dispersed. Although por-w still shows a certain positive correlation trend as a whole, the number of samples deviating from the reference line increases significantly, indicating that the inversion stability of water-bearing porosity under strong noise begins to weaken.

The inversion effect of por-c is the worst at this noise level. Scatter points are widely distributed throughout the value range, and some points are even close to the parameter boundary, showing obvious instability. This shows that under the current P-S model and frequency conditions, the dispersion response characteristics of clay volume fraction are strongly coupled with other parameters. Once the input data is polluted by noise, the inversion results are prone to large fluctuations.

In contrast, por-p still maintains a relatively good linear distribution. Although the scatter points begin to appear discrete, the overall distribution is still around the reference line, indicating that the volume fraction of pyrite still has good anti-interference ability under 5 % noise conditions.

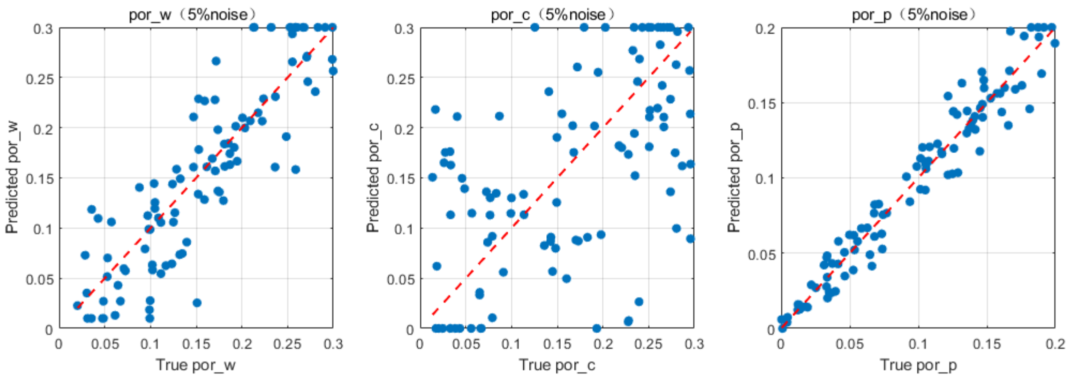

Fig. 7 Scatter point distribution under 5 % noise

As shown in Figure 8, when the noise level increases to 10 %, the three-parameter inversion results are significantly affected, but the degree of degradation of different parameters is still different. At this time, the scatter points of por-w have obviously deviated from the reference line, especially in the middle and high value areas, indicating that the inversion accuracy of water-bearing porosity decreases significantly under high noise conditions.

Por-c almost loses a stable linear correspondence at 10 % noise level, and the scatter distribution is extremely discrete, and more sample points are concentrated near the upper and lower boundaries of the parameters, indicating that the PSO algorithm has a significantly weaker ability to identify the clay volume fraction during inversion, and the noise has caused strong interference to its inversion process.

Compared with the former two, the inversion results of por-p still show relatively good stability. Although the scatter points are more dispersed than those under low noise conditions, they are still distributed near the reference line in general, indicating that the volume fraction of pyrite still has certain anti-interference ability under strong noise conditions.

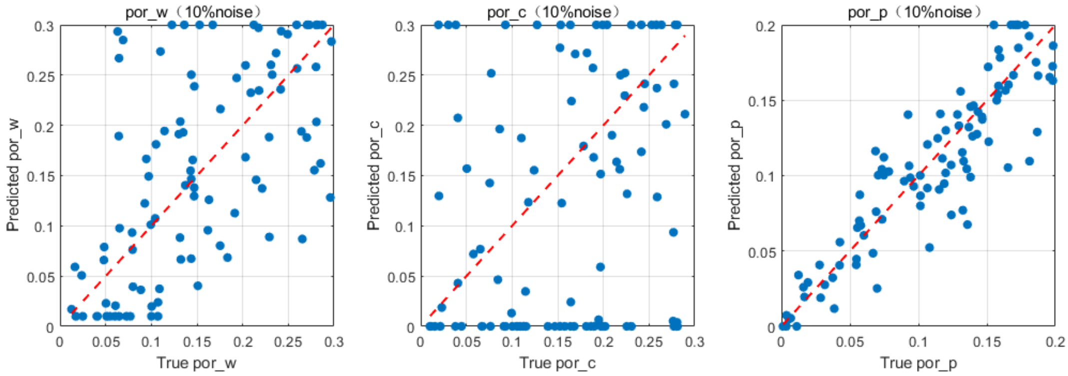

Fig. 8 Scatter point distribution under 10 % noise

It can be seen from the four groups of figures that as the noise level increases from 1 % to 10 %, the accuracy of the three-parameter inversion generally shows a downward trend, but the rate of decline is not consistent. In general, the anti-noise performance of the three parameters can be summarized as follows: por_p＞por_w＞por_c

The main reason for this difference is that pyrite, as a conductive mineral, has obvious influence on the dispersion response, which is easier to be identified under the combined constraints of multi-frequency conductivity and dielectric constant. The water-bearing porosity directly affects the proportion of the host phase and has a strong control effect on the overall response, so its anti-noise performance is also good. The clay volume fraction in the model is mainly reflected in the surface polarization effect of non-conductive particles. The influence mode is more complex, and there is a certain coupling with other parameters. Therefore, error accumulation and instability are more likely to occur under noise interference.

In addition, it can be observed from the diagram that at higher noise levels, the predicted values of some parameters gradually gather to the upper and lower boundaries. This shows that when the observation data is polluted by strong noise, the PSO algorithm is more susceptible to the local disturbance of the objective function in the search process, resulting in boundary effect. This phenomenon is most obvious on por-c.

4. Summary

In this paper, a reservoir parameter inversion method based on P-S model is established. The results show that the PSO algorithm can realize the effective inversion of oil and gas saturation and related parameters in the model, and the accuracy can reach 99 %. The PSO algorithm is iteratively optimized one by one, and the processing time is linearly related to the number of samples. Based on the P-S model, the processing time of a single group of samples is within 0.5 seconds. Then the stability and anti-interference ability of the model under 1 %, 3 %, 5 % and 10 % noise levels were analyzed. By introducing different intensity noises and comparing the prediction results of different parameters, it can be seen that the method established at the 5 % noise level is still stable, while the processing results have a large deviation at the 10 % noise level. In summary, this paper focuses on the analysis of dielectric dispersion model and saturation evaluation of shale oil and gas reservoirs, establishes a research framework from theoretical basis, model analysis to practical evaluation application, and verifies the feasibility of combining P-S dispersion model with PSO algorithm in shale reservoir parameter evaluation. The research results show that the multi-frequency dielectric logging has a good application prospect in the evaluation of oil and gas saturation in complex reservoirs. Combined with the

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applicable dispersion model and the appropriate inversion method, it can provide new technical ideas and method support for the fine evaluation of shale reservoirs.

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